Explainable AI for Recommender Systems

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03.06.22

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Agenda

- What are Explainable Recommender Systems?
- Literature review questions
- Methods
- Results
- Synthesis table
- Design of a Taxonomy
- Conclusion

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What are explainable Recommender Systems?

[1,6,7,11]

Recommender Systems

Explainable Artificial Intelligence

Explainable Recommender Systems

3

Literature review Questions

- Q1: Which modalities can be used to convey explanations to the end-user in Explainable Recommender Systems (ERS) ?
- Q2: How (persuasive) explanations can increase acceptance rate of ERS ?

4

Methods

- Scopus
  - (TITLE-ABS-KEY (explainable AND recommender AND systems) AND TITLE-ABS-KEY (energy AND efficiency))
    - Resulted with 5 articles
  - TITLE-ABS-KEY (explainable AND recommender AND systems)
    - Resulted in 315 articles
- 12 -15 recent and interesting articles selected

Results from the literature review

<u>Criteria to build ERS</u>

- W-problem
- Recommendation Models
- **Explanation modalities**
- Input data
- Computing platforms
- **Evaluations techniques**

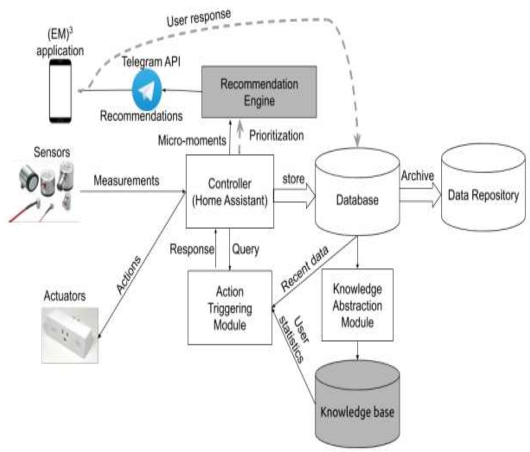
Elements ERS explanations answers: [1,2,6,7,11]

- **What**
- Who
- Weather
- When
- **Why**
- Where

W-Problem

Models used to predict ‘WHAT’ and ‘WHY’ [4,5,7,8,9,10,13]

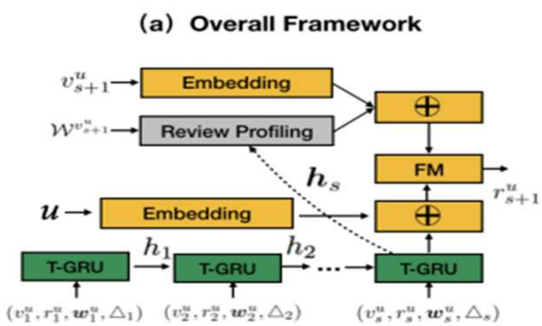
- Rule based
- Context based
- Fusion based
- Neural networks
- Collaborative Filtering
- Knowledge graph



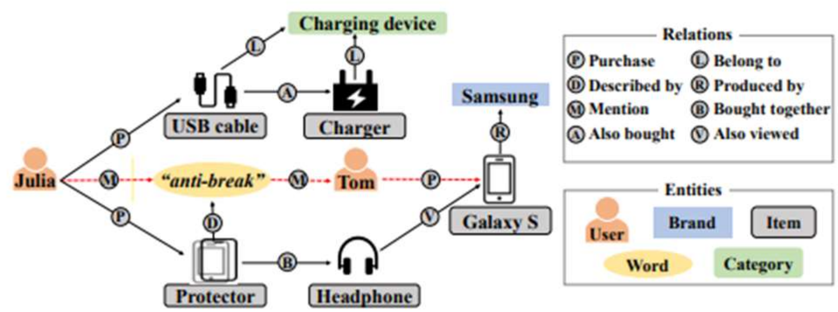
Energy model [7,8,9]

$$\textsc{SimUsers}_{CF}(u_1, u_2) \wedge \textsc{Listens}(u_1, a) \Rightarrow \textsc{Listens}(u_2, a)$$
$$\textsc{SimArtists}_{CF}(a_1, a_2) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2)$$
$$\textsc{SimArtists}_{last.fm}(a_1, a_2) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2)$$
$$\textsc{SimArtists}_{content}(a_1, a_2) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2)$$
$$\textsc{HasTag}(a_1, t) \wedge \textsc{HasTag}(a_2, t) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2)$$
$$\textsc{SimFriends}(u_1, u_2) \wedge \textsc{Listens}(u_1, a) \Rightarrow \textsc{Listens}(u_2, a)$$
$$\textsc{PopularArtist}(a) \Rightarrow \textsc{Listens}(u, a)$$
$$\neg\textsc{Listens}(u, a)$$

Rule based in Music [5,10]



Dynamic Explainable [4]

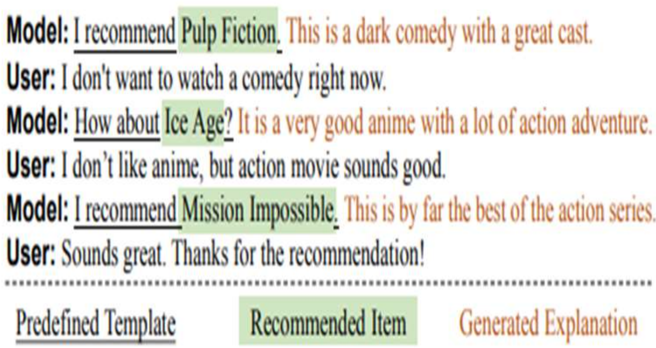


Knowledge graph with SA [13]

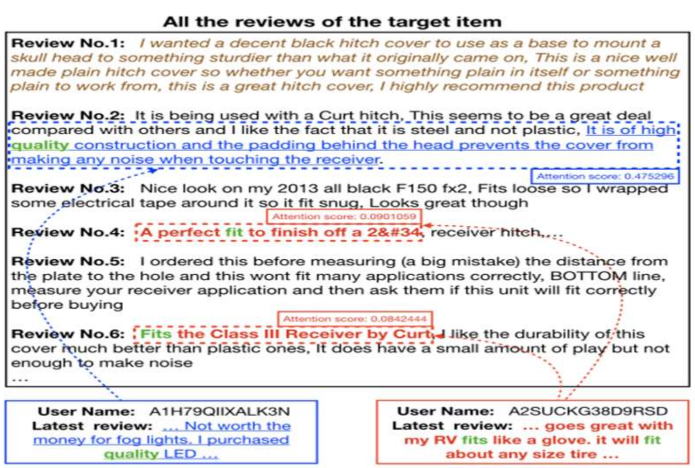
Recommendation Models

Q1:Different Modalities used to explain 'WHY' [2,3,4,5]

- Textual
- Visual
- Hybrid
- Social
- Item /user factor



Factor	Style	We recommend *Shake It Off* by *Taylor Swift* because:
Personal factor	P-first	Exactly *five years* have passed since you listened to it for the first time.
	P-last	Exactly *three years* have passed since you listened to it last.
	P-together	Around the same time, you frequently listened to it and *Applause* by *Lady Gaga*, which you listened to just now.
	P-total	You will have played it *100* times when you listen to it next.
Social factor	S-total	Its total play count by all users reached *one million*.
	S-unique	The number of unique users who listened to it reached *100 thousand*.
	S-favorite	The number of users who added it to their Favorites reached *10 thousand*.
Item factor	I-release	Exactly *five years* have passed since it was released.
	I-live	*Today, Taylor Swift* performed it at a live concert.



	Target Item	Textual Review	Visual Explanation VECF(-rev)	Visual Explanation VECF
1		I loved about the previous generation and ***expanded the toe box a little to improve the fit.*** great buy, highly recommended.	[x=13, y=13]	[x=9, y=1]
2		***They fit my stubby fingered hand pretty well.*** I bought the large and my hand measured 9.25&34 at the knuckles.	[x=10, y=5]	[x=3, y=1]
3		These sunglasses fit well and ***I like the design around the nose***; they sit rather than dig like most other glasses can. The included pouch is great for keeping your glasses safe and scratch free.	[x=6, y=11]	[x=7, y=6]
4		The cap, which is made of a fairly heavy fabric, makes the head feel hot when worn for several hours in a warm gym or outside on a warm day. I, therefore, tend to wear it only when it is cold outside . -bi	[x=13, y=13]	[x=1, y=1]
5		These are comfortable and are a great value. I like the waist band and they are so so so (more words) comfortable....; -)-bi	[x=10, y=6]	[x=4, y=4]
6		The fabric is amazingly soft and the fit is perfect. I own several items from next level and will continue to add to my collection with different colors and styles. Amazing company, Amazing product.	[x=3, y=7]	[x=1, y=5]

Explanation modalities

Additional side information for ‘WHY’ [12]

- User reviews
- Item reviews
- Sensor readings

Tradeoff :

- Latency
- Computationally expensive

Input data

Where to deploy ERS: [6,8,9]

- Edge servers
  - Safer
  - Privacy
  - More expensive
- Cloud servers
  - Less expensive
  - Latency
  - Dependency on Internet
  - Vulnerable

Computing platform

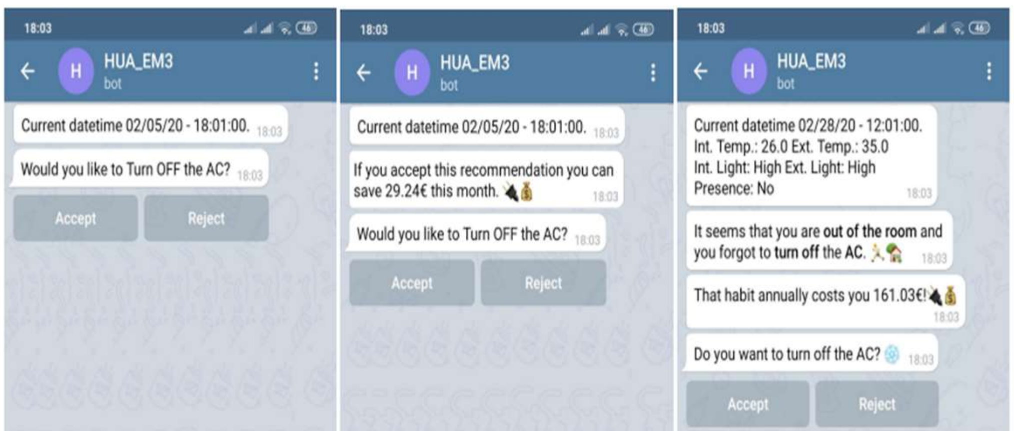
Q2: How 'WHY' increases acceptance rate in ERS [1,6,11]

- Offline or dead test
  - Data split to 80% (train) and 20% (test)
- Online or live test

- User Study
  - Scenario presented

Measurements:

- Quantitative
  - Accuracy, Precision, Recall, MAE, NDCG
- Qualitative
  - Quality of explanation
- Ablation

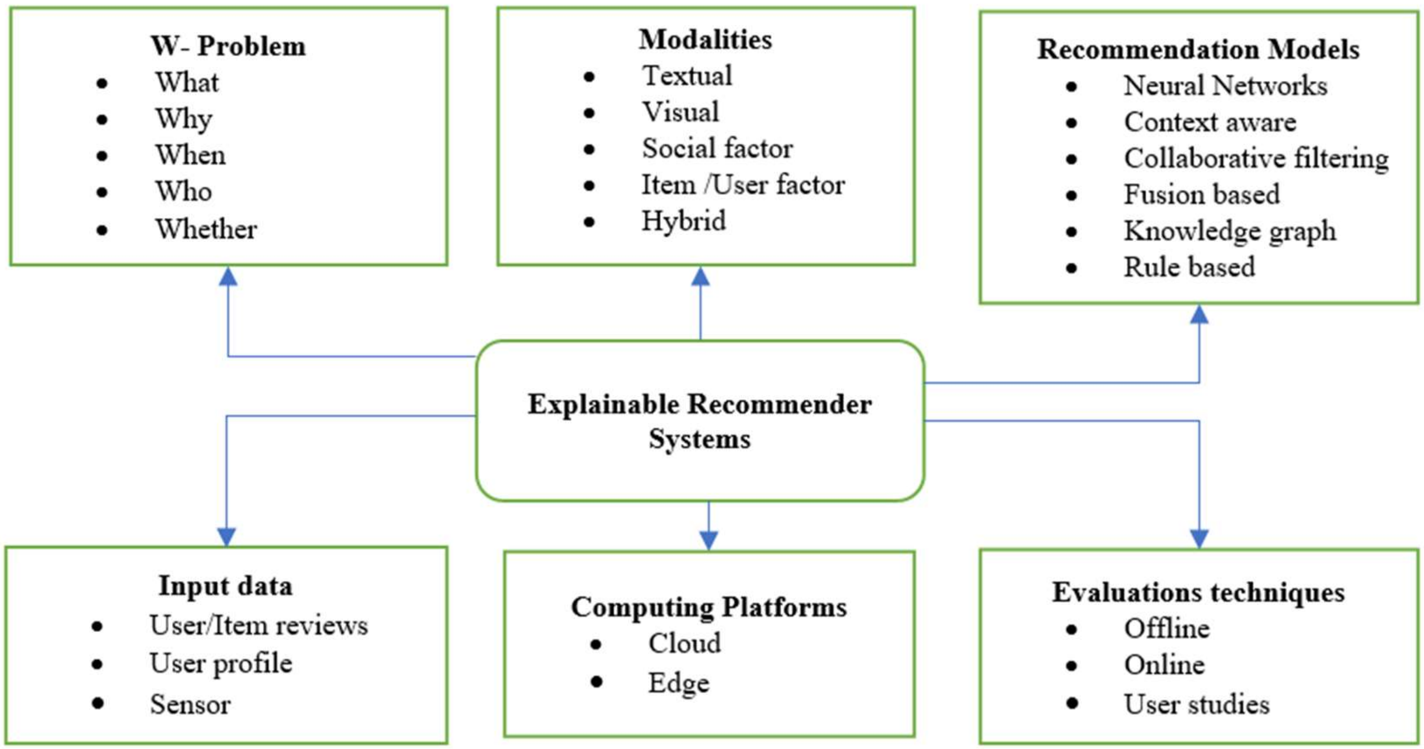


(a) (b) (c)

Synthesis

	Towards Conversational Explainability	Personalized Fashion Recommendation with Visual Explanations based on Multimodal Attention Network	Dynamic Explainable Recommendation Based on Neural Attentive Models	Delivering explainable and personalized recommendations for energy efficiency	Smart fusion of sensor data and human feedback for personalized energy-saving recommendations	Intelligent edge-based recommender system for internet of energy applications	Explainable Recommendation for Repeat Consumption	Personalized Explanations for Hybrid Recommender Systems	Reinforcement Learning over Sentiment-Augmented Knowledge Graphs towards Accurate and Explainable Recommendation
Year	2020	2019	2019	2020	2021	2021	2020	2019	2022
Aim	Explanation through multi-turn feedback	Explanation by highlighting point of interest on an image	Explanation considering users current state of mind.	Persuasive explanation for energy management	Persuasive explanation using fusion based RS	Persuasive explanation by performing computation in edge servers to avoid information leakage	Explaning repeat consumption songs based on social, item, personal factors	Provides real time recommendation with 7 textual explanations	Uses sentiment analysis to provide explanation
Concept	Context aware	Collaborative Filtering	Context aware	Context aware	Data fusion	Edge/fog based hybrid RS	Hybrid	Hybrid	Knowledge graph RS
W problems	we	why, what	when, what, why	Why , what	Why , what	Why , what	who , what , why	who, what, why	why , what,who
Recommendation models	Multi-task learning framework, multiview feedback integration	Fine grained visual preference modeling , GRU on user review to form multimodal attention network	Time aware GRU-user profile, CNN- user review	Action Triggering model,Knowledge Base, Recommendation engine	stacked LSTM Neural network, for fusion of data	stacked LSTM Neural network	Probabilistic soft Logic, using rule based explanation	Probabilistic soft Logic, using rule based explanation	Uses KG to explain the reason, by using sentiment analysis..
Personalized	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Human-in-the-loop	Yes	-	-	Yes	Yes	Yes	-	-	Yes
Explanation modality	Textual explanation	Visual explanation	Visual explanation	Contextual and textual explanation	Contextual and textual explanation	Home assistant UI, textual /visual explanation	Textual explanation with social and Item, user explanation	Textual explanation with social and Item, user explanation	Interactive UI with Textual explanation
Evaluation (offline/online)	Offline datasets (amazon)	Offline datasets (amazon)	offline/user study	user studies	Online (EM3)	Online(EM3)	user studies	user studies along with online(lastfm)	Offline datasets (amazon), user studies
Evaluation: Quantitative	HR, NDCG, MRR- for prediction.	HR and NDCG	RMSE- for prediction explanation	Accuracy of prediction	Accuarcy of prediction	Decrease in latency			NDCG, HR,F1, Precision, Recall
Qualitative	3 experts to study explanation,	Acceptance rate	Personalized explanations increases acceptance rate	Persuasive explanation increases acceptance rate	Persuasive explanation increases acceptance rate	No data loss	P total persuades users	No of explanations and styles are compared	User study- compare explanations between models
Input data	User / item reviews	User / item reviews	User / item reviews	user profile, context	user profile, context	user profile, context	item/user/social info	item/user/social info	User / item reviews
Computing platform	-	-	-	-	Cloud Servers	Edge Server	-	-	-
Ablation	Yes	Yes	No	No	No	No	No	No	Yes

Design of a Taxonomy for ERS[7,14,15]



Conclusions

How to build ERS Model ?

- W-problem
- Recommendation Models
- Explanation modalities
- Input data
- Computing platforms
- Evaluation techniques

Contribution :
Designed a Taxonomy

Limitations:

- Is not an extensive study, further criteria can be added.

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Thank You !!!

Questions?

Explainable AI for Recommender Systems

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